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**MULTI-SCALE FRACTAL ANALYSIS OF IMAGE TEXTURE AND PATTERN**

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## **Introduction**

Fractals embody important ideas of self-similarity, in which the spatial behavior or appearance of a system is largely independent of scale (5). Self-similarity is defined as a property of curves or surfaces where each part is indistinguishable from the whole, or where the form of the curve or surface is invariant with respect to scale. An ideal fractal (or monofractal) curve or surface has a constant dimension over all scales, although it may not be an integer value. This is in contrast to Euclidean or topological dimensions, where discrete one, two, and three dimensions describe curves, planes, and volumes. Theoretically, if the digital numbers of a remotely sensed image resemble an ideal fractal surface, then due to the self-similarity property, the fractal dimension of the image will not vary with scale and resolution. However, most geographical phenomena are not strictly self-similar at all scales, but they can often be modeled by a stochastic fractal in which the scaling and self-similarity properties of the fractal have inexact patterns that can be described by statistics. Stochastic fractal sets relax the monofractal self-similarity assumption and measure many scales and resolutions in order to represent the varying form of a phenomenon as a function of local variables across space.

In image interpretation, pattern is defined as the overall spatial form of related features, and the repetition of certain forms is a characteristic pattern found in many cultural objects and some natural features. Texture is the visual impression of coarseness or smoothness caused by the variability or uniformity of image tone or color. A potential use of fractals concerns the analysis of image texture. In these situations it is commonly observed that the degree of roughness or inexactness in an image or surface is a function of scale and not of experimental technique. The fractal dimension of remote sensing data could yield quantitative insight on the spatial complexity and information content contained within these data (2). A software package known as the Image Characterization and Modeling System (ICAMS) (6) was used to explore how fractal dimension is related to surface texture and pattern. The ICAMS software was verified using simulated images of ideal fractal surfaces with specified dimensions. The fractal dimension for areas of homogeneous land cover in the vicinity of Huntsville, Alabama was measured to investigate the relationship between texture and resolution for different land covers.

## **Methodology**

The isarithm or line-divider method (3) for calculating fractal dimension was used in this analysis due to its robustness, accuracy, and its relative lack of sensitivity to input parameters. In this method, the fractal dimension of a curve (in a two-dimensional case) is measured using different step sizes that represent the segments necessary to traverse a curve. For an irregular curve, as the step sizes become smaller, the complexity and length of the stepped representation of the curve increases. For surface representations (such as remotely sensed images), the isarithm method uses contours of equal  $z$  values as the objects of measurement whose fractal dimensions are estimated. The contours or isarithms are generated by dividing the range of pixel values into a number of equally spaced intervals. For each resulting isarithm line, the image is divided into two regions--areas above and below the isarithmic value. Each isarithm's length (as represented by the number of edges in a grid representation of a surface) is then measured at step sizes up to a user specified maximum. The logarithm of the number of edges is

regressed against the log of the step sizes and the slope of the regression is used to calculate the fractal dimension, resulting in a unique value of  $D$  for each isarithm. The fractal dimension of the entire image is calculated by averaging the fractal dimensions of each isarithm.

### Huntsville Texture Analysis

High resolution imagery of the Huntsville, Alabama area was used to evaluate the differences in fractal dimension that occur among textures associated with differing land covers. Mission M424 conducted by the Lockheed Engineering and Science Company collected 10 meter resolution data using the Advanced Thermal and Land Applications (ATLAS) sensor system mounted in a NASA Learjet, (4). The collection date was 7 September, 1994, a clear day with less than 5 percent cloud cover. ATLAS is a 15 channel imaging system which incorporates the bandwidths of the Landsat Thematic Mapper with additional bands in the middle reflective infrared and thermal infrared range. 384 x 384 pixel images containing homogeneous land uses were obtained from the 10 meter ATLAS data set. Three land uses were analyzed: 1) an agricultural area located north of Huntsville; 2) a forested area located in the mountains to the southeast of town; and 3) an urban area containing the central business district and adjacent commercial/residential areas. The agricultural area contains large cotton fields and pastures devoted to grazing, with a sparse road network oriented generally along the cardinal directions. The image of the forested area is fairly uniform, since the 10 meter resolution is insufficient to resolve individual trees. Topographical features such as the valley extending from the northwest corner to the south central part of the image are the main distinguishing features. The urban image is highly complex, with individual streets and buildings clearly visible.

The Normalized Difference Vegetation Index (NDVI) was computed for the agricultural, forest, and urban images at 10 meter resolution (384 x 384 pixels) and for resampled images at 20, 40, and 80 m resolution using an image pyramid approach (1). NDVI was computed from resampled images in ATLAS channels 6 (near infrared) and 4 (red) using the following formula:

$$[1] \quad \text{NDVI} = (\text{ch6} - \text{ch4}) / (\text{ch6} + \text{ch4})$$

NDVI varies from -1 to +1, and provides a good indication of the amount of photosynthetically active biomass in the image. Snow, water, clouds, moist soil, and highly reflective non-vegetated surfaces generally have NDVI values less than zero, rock and dry soils have values close to zero, and highly vegetated surfaces have indices close to +1.0. NDVI varies across spatial extents in a complex fashion due to influences of the varying domains of topography, slope, availability of solar radiation, and other factors (7). The NDVI values were rescaled to an 8 bit format to facilitate comparisons between the three land cover textures. The image size and the range of resolutions analyzed was limited at the upper end by the need to get a homogeneous land cover (thus limiting the maximum size of the image) and at the lower end by the minimum image size (48 x 48 pixels) necessary to use five steps in the isarithm method of computing fractal dimension.

Increasing the pixel size from 10 to 80 meters affected the non-spatial variance of the three land covers in different ways (Table 1). Variance dropped by a moderate amount for the

agricultural image and by a greater amount in the forested image, but it changed very little for the urban image. Moran's *I* spatial statistic dropped as resolution decreased from 10 to 80 meter pixels in the agricultural and urban images (indicating decreasing spatial autocorrelation), and *I* increased then declined in the forested image. These measures provide indications that the resampling process (and by extension, imaging at different resolutions) affects both the non-spatial distribution of the values in an image as well as the relationships between features in the image.

**Table 1. Descriptive Statistics--Huntsville NDVI Texture Analysis**

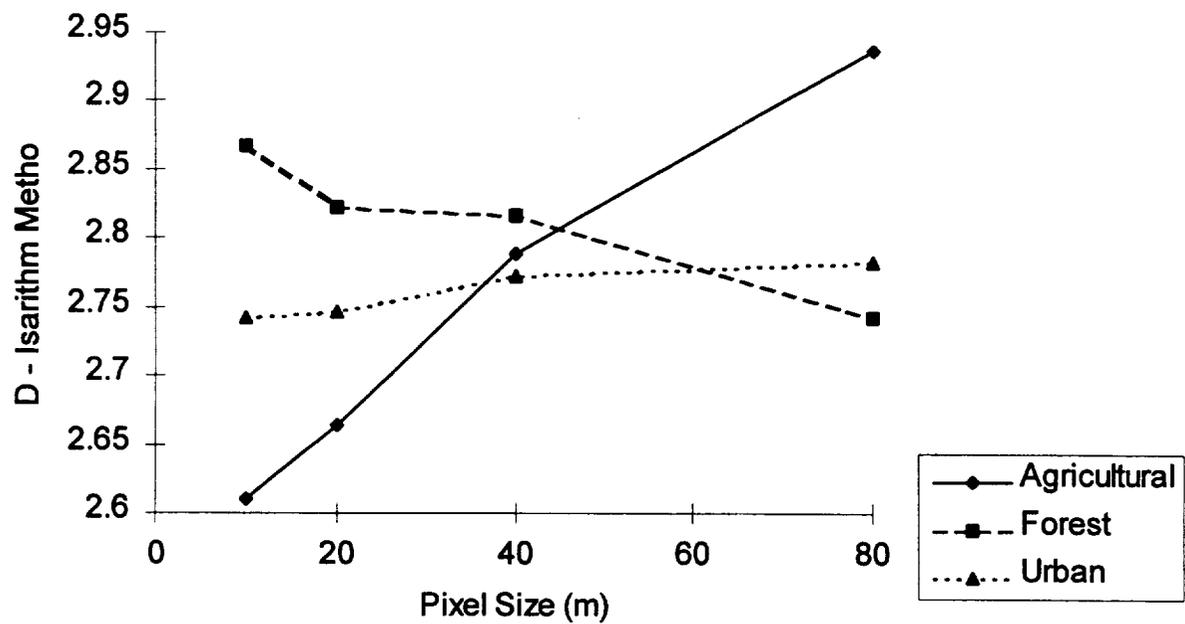
Land Cover	Resolution	D	Mean	Median	Std. Dev.	Moran's I
Agricultural	10	2.6101	127.10	137	42.18	0.9023
	20	2.6640	127.13	137	42.10	0.8763
	40	2.7893	127.15	136	41.97	0.8217
	80	2.9371	127.22	134.5	41.79	0.7369
Forest	10	2.8667	127.73	132	38.68	0.7557
	20	2.8229	127.86	132	38.19	0.7830
	40	2.8159	127.89	131	37.73	0.8073
	80	2.7419	128.02	131	37.53	0.7932
Urban	10	2.7417	127.01	137	42.50	0.7587
	20	2.7471	127.00	133	42.50	0.7595
	40	2.7734	126.99	132	42.50	0.7063
	80	2.7829	127.00	133	42.51	0.6726

The ICAMS isarithm method with step size of five and contour interval of 10 was used to compute fractal dimension for the three land uses. Unlike the ideal fractal surfaces, real world images are rarely self-similar, so one would expect fractal dimension to vary with the resolution of the sensor. The slope of the changes in *D* with changes in resolution for the three land uses indicates how agricultural, urban, and forested areas compare over the range of pixel sizes considered. Figure 1 shows that over the 10 to 80 meter range of resolutions, the agricultural image *D* increases from just over 2.6 to more than 2.9. The forest image shows a general decline in *D* with decreasing resolution, and resampling the 10 meter resolution image has only a small negative effect on the computed *D* value. The forested scene behaves as one would expect—larger pixel sizes decrease the complexity of the image as individual clumps of trees are averaged into larger blocks. It is likely that the complexity of the forested image (as indicated by a higher *D* value) would increase if the sensor were able to resolve individual trees within the scene. A linear regression on the three land cover responses leads to the conclusion that the urban image behaves most like an ideal fractal surface and can be said to be self-similar over the range of pixel sizes analyzed, since one cannot reject the hypothesis that the slope of the pixel size-fractal dimension relationship is equal to zero. The 95 percent confidence interval for the regression slope overlaps zero (although just barely at the low end). It should be noted, however, that these regressions are based on only one image and four pixel sizes in a limited range for each land

cover type. Although the  $R^2$  values for the agriculture and forest images is 0.94 or higher, the regression of the urban resolution- $D$  relationship is 0.87 which is not as strongly linear.

The increased complexity of the agricultural image with increasing pixel size results from the loss of homogeneous groups of pixels in the large fields to mixed pixels composed of varying combinations of NDVI values that correspond to roads and vegetation. As resolution decreases in the agricultural image, the roads tend to appear wider and the fields are smaller, until eventually the image appears very complex, with few homogeneous areas. This is also reflected in the changes in Moran's  $I$  statistic in Table 1. The  $I$  statistic for the agricultural area drops from near +1.0 (indicating a high level of spatial autocorrelation) to 0.74, indicating a more dispersed spatial arrangement of values in the image as resolution grows more coarse. The same process occurs in the urban image to some extent, but the lack of large, homogeneous areas in the high resolution NDVI image means the initially high  $D$  value is maintained as pixel size increases.

**Figure 1. Fractal Dimension of Huntsville NDVI Images**



**Conclusions**

In the example presented here, the complexity of NDVI images of agriculture, forest, and urban areas responds differently to aggregation. The image of the agricultural area grew more complex as the pixel size increased from 10 to 80 meters, while the forested area grew slightly smoother and the complexity of the urban area remained approximately the same. In examining the changes in fractal dimensions with changing pixel size, an obvious question to ask is whether it is best to use a fine resolution for analyzing complex scenes with heterogeneous land uses, or is it best to select a resolution where the complexity of each land cover is approximately the same

(around 40 meters resolution). If one is wishing to distinguish between the different land covers, then the resolution at which the greatest differences in complexity occur may provide the maximum discrimination between land covers. If the question is concerned with determining lumped characteristics of a heterogeneous scene, then the resolution with the least differences in fractal dimension between land covers will likely provide more unbiased estimates of the scene taken as a whole.

More research is needed to examine how the complexity of a geographical process having a known spatial domain is depicted in remotely sensed images. This process domain benchmark would allow significance testing of the fractal dimension's response to changes in resolution. Processes that are more scale independent (closer to the monofractal ideal) require fewer data (i.e., lower resolutions) than other processes that are highly scale dependent. No one resolution is optimal for all research questions, so further investigation is needed to determine how the fractal dimension can be used to provide indications of the tradeoffs involved in selecting the scale, resolution, and spatial extent of the input imagery.

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